AUTONOMOUS MAP LEARNING FOR A MULTI-SENSOR MOBILE ROBOT USING DIKTIOMETRIC REPRESENTATION AND NEGOTIATION MECHANISM

G. Borghi*+ and D. Brugali*•

* PM-AI&R Project - Dipartimento di Elettronica e Informazione
Politecnico di Milano P.za Leonardo da Vinci, 32 - 20133 Milano, Italy

+ Institute LADSEB of CNR (National Research Council of Italy)
Corso Stati Uniti 4, 35020 Padova, Italy

• Dipartimento di Elettronica e Informazione, Politecnico di Torino
Corso Duca degli Abruzzi , Torino, Italy

phone : +39 2 2399 3622; Fax : +39 2 2399 3411; E-mail: {borghi, brugali}@elet.polimi.it

Abstract - *In this paper we present a method for a multi-sensor mobile robot to explore autonomously an unknown environment. The method tries to solve the main problems involved by such a task. In particular we present a model to represent geographic knowledge, based on an extension of the "Diktiometric representation" of Engelson and McDermott [1]. We paid special attention to the maintenance of this model, providing mechanism to allow the consistent fusion of sensory observation. Furthermore we argue that, due to the different capabilities of the devices of a multi-sensor system, the only interaction between the sensors should be indirect and based on the individual effect that each sensor has on the system controller. Therefore we present a negotiation mechanism allowing to integrate the world knowledge represented in different models, each of which is updated with the sensory information provided by a specific devices. In our work this integration involves only the exploration strategies of each representation.*

1. INTRODUCTION

Several new applications, such as planetary navigation, construction, toxic waste cleanup and even office automation require the autonomous mobile robot to be able to operate in unstructured environments with little a priori information. To achieve this ability the autonomous robot must exhibit higher degrees of autonomy by being able to recover robust and consistent descriptions of its surroundings using sensory information; this kind of task is commonly called exploration of an unknown environment (see for example [7], [3]).

In order to effectively support the goal of acquiring autonomously a world model, the robot must exhibit several characteristics:

- it must be able to manage a variety of sensors; rarely a single sensor system is enough to the exploration task;
- it must provide mechanisms to manage the uncertainty due to the limitations of the sensor devices;
- it must be able to recover the uncertainty on its position due to the limitations of the actuators;
- it must provide exploration strategies in order to plan autonomously the sequence of actions allowing to execute the task.

In recent years, several approaches to the robot exploration have been proposed. The issue of representing sensory information in a complete and consistent manner is one of the most challenging problems faced by the research community.

The geometric approach to world representation attempts to build a detailed metrical description of the environment from sensor data (see for example [2], [6], [9]). This kind of representations has a reasonably well-defined relation to the real world, but is highly vulnerable to metrical inaccuracy in sensory devices and movement actuators.

The "Occupancy Grid" [5] framework represents a fundamental departure from traditional geometric approaches. It uses a stochastic tessellated representation of spatial information maintaining probabilistic estimates of the occupancy state of each cell in a spatial lattice.

Other works [3], taking a more qualitative approach, show great promise of overcoming the fragility of purely metrical methods: they consist in a topological description of the environment. The model is a network of nodes, where nodes represent distinctively recognizable places in the environment, and arcs represent control strategies which take the robot from one place to another.

Diktiometric representations [1] broaden the topological representation to include the paths' shapes, i.e. the geometric relations between places. In [1] only "pointlike" places are considered.

The aim of this paper is to present a new approach to the exploration task for an autonomous robot, trying to solve the above mentioned problems.

For sake of brevity, in this paper we will just focus on a few issues involved in our work:

- world modeling: we present an extension of the "diktiometric representation" of Engelson and McDermott [1];
- observation fusion: we present an approach to solve the problem of preserving consistency in updating the robot world model;
- exploration strategies: we present how the robot is able to plan autonomously the sequence of actions that allows it to execute the task.
- a negotiation mechanism allowing the integration of different exploration strategies.

In our "diktiometric representation" places may be either single "local views" or "extended views", that is sets of merged local views referred to a single reference frame attached to the place. The whole representation is a network of 2D geometrical representations connected by arcs with geometric relations between places. In each extended view the uncertainty about features is locally bounded.

Our approach to build extended view is based on the Move->Sense->Model->Match->Merge cycle. When new features have to be merged in an extended view, their parameters must be expressed in the reference frame of the extended view. This needs relations (called "external relations") that are affected even with uncertainty on the robot location.

To keep low uncertainty we introduce in the merging process "internal relations". Internal relations specify distances between corners or angular widths between edges belonging to the same visual scene; therefore their measurements are affected only with the uncertainty of the sensor system and not on the robot location. Measurements about internal and external relations are used to obtain a new estimate of the parameters.

The theory outlined in this paper is implemented in a project called EXPLORER. In this project we investigate how a multi-sensor autonomous robot can explore a "large scale" environment. We mainly are interested in multi-sensor integration rather than multi-sensor fusion, unlike Durrant-White [2], Elfes [5]. We argue that the only interaction between the sensors may be indirect and based on the individual effect that each sensor has on the system controller. EXPLORER does not try to build a single consistent representation of the environment using information provided from different sensor devices; it rather tries to build a coherent set of descriptions, that are independently consistent. In EXPLORER the responsibility to manage the different sensory information is distributed among several "representation agents". Each representation agent is a module, belonging to a blackboard-based distributed control architecture, which builds a private description of the environment using sensory observation provided by a specific device. Our aim in EXPLORER is to investigate how to integrate the world knowledge of every agent and in particular how to take into account the different requirements of their exploration strategies. We use a negotiation process among modules, called Proposal Mechanism, described in Section 4.

A first prototype of EXPLORER has been implemented and is currently under assessment. At the moment EXPLORER utilizes two "representation agents", maintaining two different world models: an "Occupancy Grid", as defined by Elfes [5], and our extension of the "Diktiometric Representation" of Engelson-McDermott [1]. Anyway the architecture allows to introduce new "representation agents" as new sources of information are available.

The paper is organized as follows. Section 2 introduces the LASMAP agent and our version of the "Diktiometric Representation". Furthermore we explain how this kind of model is useful even for reducing robot position uncertainty and how we face the problem of integrating sensory observations acquired from different points of view in a consistent manner. Section 3 briefly presents the second representation agents and its exploration strategy. Section 4 presents the system architecture and a general negotiation process, which allows the collaboration among every kind of system agents. Section 5 draws some conclusions.

2. THE DIKTIOMETRIC REPRESENTATION

The first representation agent, called LASMAP, uses the information provided by a telemeter device composed of a laser range finder and a rotary table allowing the laser to rotate around a vertical axis. Each telemetric reading provides the distance of the nearest obstacle in front of the telemeter device.

The world representation is built merging a sequence of consecutive 2D visual scenes, where a visual scene is a geometric description of the environment built using sensory data acquired from a single robot position. A visual scene is related to the robot reference frame and henceforth it will be called "local view". The basis elements of this representation are corners joining pairs of edges describing the boundaries of the detected objects.

The main problem in such world-modeling is to compute the relative position of features (i.e., corners) observed from different points of view in order to merge them in a consistent manner. LASMAP uses only geometric characteristics of detected objects to find correspondences among their features and then the relative position. LASMAP doesn't rely on the odometric system as in [5] and [6] and it doesn't make use of visual landmarks as in [7]. The proposed self-location method (Section 2.1) shows the weakness to depend on the amount of available information, that is, the robot is obviously not able to estimate how far it traveled along a corridor, where it sees just a couple of parallel walls.

Since this weakness is common to every approach attempting to build a geometric description of the world referred to a global reference frame, LASMAP faces this limitation using an extension of the "diktiometric model" of Engelson and McDermott [1]. Engelson and

McDermott deal with a networks of places being small regions which can be treated as single points. In our “diktiometric representation” places may be either single “local views” or “extended views”, that is sets of merged local views referred to a single reference frame attached to the place.

Fig. 1 shows an example of our representation: each reference frame corresponds to a node of the diktiometric graph. The displacements between frames are the measures associated to the arcs of the graph.

The exploration process is based on a Move->Sense-> Model->Match->Merge cycle. Whenever the robot reaches a new position, it builds a local view, related to the robot reference frame, using the information provided by the laser device.

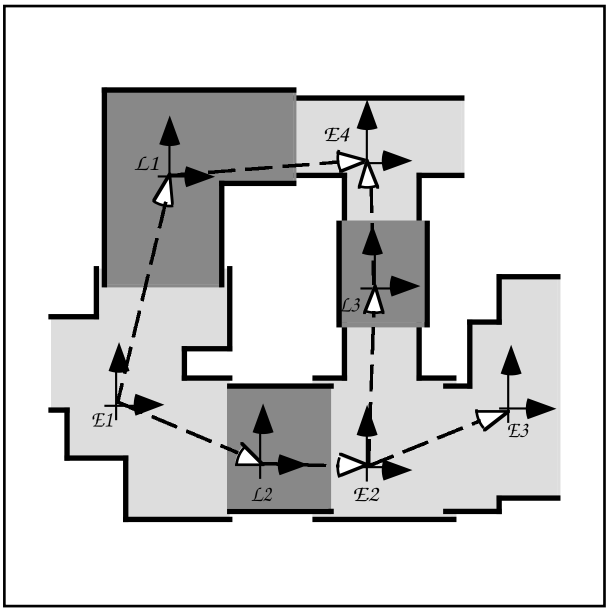

Fig. 1 - The diktiometric representation

Afterwards it tries to self-locate by matching the geometric features of the new local view with the geometric features belonging to one place of the graph so far acquired; i.e. the robot tries to estimate the displacement between the current reference frame and one attached to a place of the graph.

When the displacement is provided, the local view is merged into the correspondent place obtaining a new extended view (frames E1, E2, E3, E4 in Fig. 1).

The robot current position is related to the reference frame attached to that place. It is clear that in a diktiometric representation the robot absolute position is meaningless.

As said above, when the local view is lacking in information the robot cannot self-locate. In such a case the local view is not allowed to be merged into any place of the graph. A new place in the diktiometric graph is inserted (frames L1, L2, L3 in Fig. 1), and an arc will be created between the new place and the place to which the robot previous position was related, representing the rigid displacement between their reference frames. The displacement is computed taking into account the odometric estimation.

This way the geometric uncertainty inside a place is kept low (the robot can self-locate) and it is not propagated among different places. We chose to represent geometric uncertainty in a probabilistic way.

2.1.Matching and robot self-location

It is essential for the model consistency to know as well as possible the robot position in the real world. The odometric system supplies an estimate of the robot position/orientation, but it is not possible to rely on it.

The followed approach is based on comparisons between two visual scenes: the last local view acquired and an extended view attached to a place of the diktiometric graph. This comparison supplies correspondences among the corners of the two visual scenes.

In our representation the matching process have to compare different measurements of corners taken from different robot positions. If the matching algorithm recognizes that there is a set of correspondences among measurements of corners belonging to different point of view, they can be used to reduce the uncertainty of the displacement D existing between the two robot positions. This is done by applying the Extended Kalman Filter (Ayache-Faugeras [10]).

The matching process has mainly to satisfy the basis constraint that an hypothesis of correspondence is a one-to-one relation between the sets of corners describing the two visual scenes. The process of matching is broken into two parts: hypothesis generation, hypothesis verification.

The algorithm generates a set of hypotheses of correspondences between corners of the two visual scenes, taking into account topological and geometric properties of their objects.

Each hypothesis of correspondences is verified: a subset of correspondences between corners belonging to an hypothesis is used as measurements in the EKF to estimate the visual scene relative position.

This estimate is therefore used to verify the consistence of the other correspondences of the same hypothesis.

If the hypothesis is validated all its correspondences are used to estimate the visual scenes relative position.

In case of particular symmetries several equivalent hypotheses can be validated: it is necessary to use the odometric estimate to disambiguate them.

In the next section we show how correspondences between two visual scenes and estimates of the displacement between their reference frames are used to allow the fusion of those visual scenes.

2.2.Integrating sensory observations

When the matcher successfully individuates a consistent set of correspondences, among the corners of a new local view and the corners of an extended view of the diktiometric graph, the merger has to integrate the local view into the extended one.

For example, Fig. 2.a shows an extended view, related to the reference frame $\mathcal{E}$, and a local view, related to the reference frame $\mathcal{L}$. The matcher has identified the correspondences {(E1, L1), (E2, L2)}.

The classical approach to the fusion problem would compute, using the EKF, a new estimate of the parameters of each common corner, taking into account the two available estimates and the estimate of the displacement D between the frames $\mathcal{E}$ and $\mathcal{L}$.

Although we use a "good" estimate of the displacement D, serious fusion problem may occur. Let's suppose that in the real world there are only mutually orthogonal edges and that our sensorial system is able to measure the angular width of the corner with high precision. Let's suppose that in the so far acquired extended view, due to uncertainty propagation, there are edges e1 and e2 only roughly parallel.

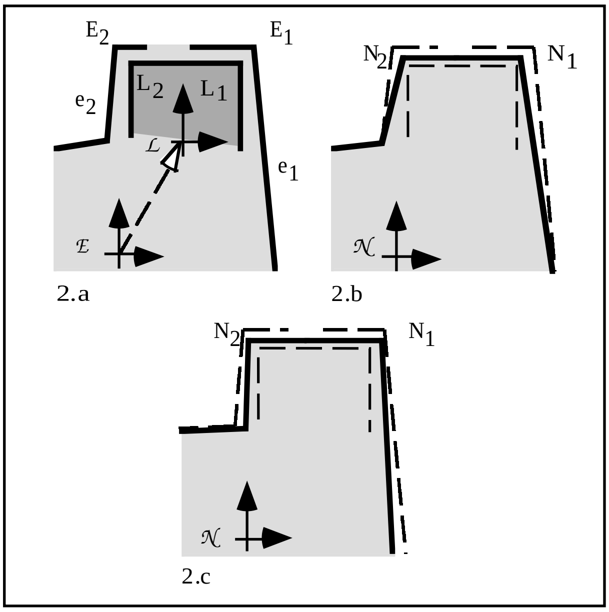

Fig. 2 - Views integration. The local view $\mathcal{L}$ is merged with the extended view $\mathcal{E}$, obtaining the extended view $\mathcal{N}$.

Following the classical approach, the fusion of E1 with L1 and of E2 with L2 would produce an extended view as showed in Fig. 2.b. in which only the parameters of these corner have been updated. The positions of corners N1, N2 was computed without taking into account the good confidence of the measurement of the angular width of the corresponding corners L1 and L2 in the local view and E1 and E2 in the extended view.

We argue that the key to obviate such a shortcoming is to introduce relations, among corners, that are independently from the displacement D and to distribute the uncertainty onto the parameters of every geometric features of the resulting extended view. The proposed solution to this problem rises from the fact that in a local view the uncertainty just depends on the precision of the sensor device. Henceforth we call relations between geometric features, such as distances between corners, angular width between edges, etc., "internal relations".

Following this approach we obtain a new extended view with a better defined relation to the real environment, where consecutive walls are quite orthogonal (see Fig. 2.c).

The merging algorithm is divided in two steps :

- building of a topological description of the resulting extended view,
- estimating the parameters of the features.

A. Building the topological description

The merger has to identify, using the set of correspondences provided by the matcher, which corners of the extended view and of the local view will appear into the new extended view.

Each corner of a local or extended view is described by a structure which stores a variety of information, such as:

- the coordinates of the corner;
- a numeric identifier;
- pointers to adjacent corners.

The topological description of the new extended view is built by computing the correct identifier of every corner and connecting adjacent corners through their identifier.

At the end of this process, every corner of the new extended view is set in correspondence with a corner of the old extended view, a corner of the local view or both. It is possible to compute the coordinates of each corner of the new extended view knowing the coordinates of its correspondent in the local view and in the old extended view.

B. Estimating features parameters

At the end of the previous step the merger has identified the topology of the resulting extended view. Now it has to estimates the parameters of any feature belonging to it. This means to estimate the new location of every corner.

Following our approach to the sensory observation fusion, the problem of estimating the corners' parameters is simply treated as a classical problem of linear regression.

Let be $c_1, c_2, \ldots, c_i, c_{i+1}, \ldots, c_{2k}$ a set of 2*k parameters to be estimated where k is the number of corners belonging to the new extended view and (c_i, c_{i+1}) are the coordinates (x, y) of the i-th corner; given furthermore a set of N linear equations of the form

$$y(t) = c_1 * u_1(t) + \ \ldots\ + c_{2k} * u_{2k}(t);$$

representing relations (internal and external) among the corners of the new extended view, where t = 1,2,...,N and $y(t), u_1(t), \ldots, u_{2k}(t)$ are the measures of 2k+1 real variable obtained in the old extended view, in the local view or both.

The estimate of the 2k parameters c_i is computed using the Markov's weighted least squares method. Let be

$$\theta = \begin{bmatrix} c_1 \\ \ldots \\ c_{2k} \end{bmatrix}$$

and $\hat{\theta}$ the estimate of θ,

$$\Phi = \begin{bmatrix} u_1(1) & \ldots & u_{2k}(1) \\ \ldots & \ldots & \ldots \\ u_1(N) & \ldots & u_{2k}(N) \end{bmatrix}; \quad y = \begin{bmatrix} y(1) \\ \ldots \\ y(N) \end{bmatrix}; \quad v = \begin{bmatrix} v(1) \\ \ldots \\ v(N) \end{bmatrix};$$

and V the covariance matrix of v, the following relation holds:

$$y = \Phi\theta + v.$$

The Markov's estimator and its covariance matrix are:

$$\hat{\theta} = \left[\Phi^T V^{-1} \Phi\right]^{-1} \Phi^T V^{-1} y; \qquad \operatorname{var}\left[\hat{\theta}\right] = \left[\Phi^T V^{-1} \Phi\right]^{-1}.$$

As said above, the merger utilizes two kinds of relation:

- external relations;
- internal relations.

External relations involve the displacements between the local view reference frames and the new extended view reference frame; therefore their measurements are affected by uncertainty on the robot location.

Internal relations specify distances between corners or angular widths between edges belonging to the same visual scene; therefore their measurements are not affected by uncertainty on the robot location.

Let's consider again the example of Fig. 2.

The local view $\mathcal{L}$ and the extended view $\mathcal{E}$ are to be merged into the new extended view $\mathcal{N}$.

The old extended view and the new one are referred to the same reference frame; furthermore it is known the displacement D between this frame and the local view reference frame.

The merger sets in correspondence the corner N2 with the corner E2 through an external relation, whose coefficients are represented in the first two rows of matrix Φ; furthermore rows 3 and 4 of Φ represent the coefficients of the external relation setting in correspondence N2 with L2:

$$\Phi = \begin{bmatrix} 0 & 0 & 1 & 0 & \ldots & 0 \\ 0 & 0 & 0 & 1 & \ldots & 0 \\ 0 & 0 & \cos(\theta) & \sin(\theta) & \ldots & 0 \\ 0 & 0 & -\sin(\theta) & \cos(\theta) & \ldots & 0 \\ & \ldots & & & \ldots & 0 \end{bmatrix},$$

$$\mathrm{y} = \begin{bmatrix} E2_x \\ E2_y \\ L2_x + a*\cos(\theta) + b*\sin(\theta) \\ L2_y - a*\sin(\theta) + b*\cos(\theta) \\ \ldots \end{bmatrix}, \quad \theta = \begin{bmatrix} N1_x \\ N1_y \\ N2_x \\ N2y \\ \ldots \\ Nk_y \end{bmatrix},$$

a, b, θ are the parameters of the displacement D.

The merger can furthermore identify internal relations, such as the distance between corners (N1, N2), whose measurement is obtained in the local view computing the distance between corners (L1, L2). In a concise way this relation can be written as follows:

$$DIST_{L1-L2} = \|N2 - N1\|.$$

Obviously these relations are to be linearized; the correspondent coefficients are inserted in new rows of the matrix Φ and the correspondent measurements in the vector y. Relations such as the distance between not consecutive corners provide constraints on angular width between edges

C. Exploration strategies

Up to now we have discussed a new way to represent geographic knowledge; but, which criteria are useful to state that the environment representation is complete?

If the robot has the possibility to circumnavigate all the visible objects in the environment, the exploration is finished when their boundaries are all represented in the "corners representation" by closed polygons.

During the exploration the robot has to deal with chains of segment representing part of boundaries. Therefore the exploration strategy has simply to complete every chain in order to build polygons.

This means to search a set of obstacle-free positions useful to see the remaining edges; the search starts in the neighborhood of every ending-corner.

As said in Section 1, our aim in EXPLORER is to investigate how to integrate world knowledge represented in different models. In the next Section we briefly describe another way to represent geographic knowledge and in Section 4 we present how to take into account the exploration strategies requirements of different world models.

3. THE SONMAP REPRESENTATION AGENTS

Using the information provided by a 24 ultrasonic sensor ring, a second agent keeps up-to-date an "Occupancy grid", as defined in Elfes [5]; it is a matrix, whose elements represent the probability that corresponding rectangular areas of the environment are occupied by obstacles. The sensory data together with a stochastic model of the sensors are used to update the probability value of every cell of the occupancy grid, following the Bayes' theory.

Every cell of the grid is initialized to the probability value 0.5: it means maximum uncertainty on the state of the world. After several successive updates, the grid may have cells with low probability to be occupied (near to 0), cells corresponding to the boundaries of the detected objects (probability near to 1), and cells representing unknown regions (probability around 0.5).

This kind of world modeling is based on strategies emphasizing additional sensing, rather than on the use of sophisticated methods to extract information from sensory data. Furthermore it doesn't allow efficient robot self-location as well recognition of previously detected places.

On the other hand, "Occupancy Grid" seems to be the most suitable world model to represent sensory data provided by sonar devices, when the sensor model takes into account the extent of the sonar beam as in [5] and even in our work.

The implemented SONMAP exploration strategy is based on the reduction of the uncertainty in the spatial information encoded in the occupancy grid. This uncertainty is computed using the cell entropy function [5]. Future positions to be explored are the maxima of this entropy function over the map.

4. COLLABORATION IN A DISTRIBUTED ARCHITECTURE

Sensory data provided by different sensor devices have to be adequately represented by specific models suitable to the kind of information to store. Anyway, due to different characteristics of every sensor devices, every model may reflects only some features of the environment, depending on the characteristic of the used sensor (the laser device is not able to detect opaque surfaces, while the sonar devices have problems to detect reflecting surfaces). In order to achieve a correct integration of the world knowledge, we developed a framework allowing to distribute among several "representation agents" the responsibility to manage different world models.

In the remainder of this section we present the underling control architecture and the negotiation mechanism allowing collaboration among different agents.

4.1.System Architecture

The EXPLORER project was developed starting from the DAAR architecture of Borghi [11]. DAAR (Distributed Architecture for Autonomous mobile Robot) is a blackboard based distributed architecture where there is not a fixed hierarchy among agents, but rather the agents establish, among them, temporary relations depending on the problem that must be solved. Each agent can collaborate with others and, when requested, it provides its capability.

Among the agents there is a blackboard: each agent can write or read information on the blackboard. It stores information of global interest, such as the current sensory measurements provided by the multi-sensor system, the state of the DAAR activity, etc. Furthermore one-to-one communication between agents is allowed by message queues. Every agent is independent from the others and has its own target to reach. They can collaborate or compete with other agents, without having a priori knowledge about existence, features and availability of the other agents.

At the moment six agents belong to the EXPLORER project, providing different capabilities, such as managing the multi-sensor system of the robot (LASER and SONAR), the graphical user interface (GUIEX), the environment representations (LASMAP and SONMAP) and the agents' coordination (EXPLORER). Other agents belong to the DAAR architecture, such as a path-planner (PP) and a robot motion manager (MOVE).

When an agent is not able to achieve its own goal, it asks the architecture for collaboration. The other agents, while pursuing their goals, may offer a contribution to a shared solution. For instance, EXPLORER is not able to decide where to bring the robot in order to improve the system world knowledge; therefore it asks the collaboration of the architecture: LASMAP and SONMAP will formulate a set of proposal, whereas the other agents will reply with a refusal message.

Subsequently, when an acceptable proposal is found, EXPLORER request the collaboration of the path-planner PP and of the robot motion manager MOVE to bring the robot in the correspondent position.

Let's now look at which level the robot system may take advantage of the different world knowledge of the "representation agents". Using their strategies they may just generate a set of proposal of "interesting" positions to reach, where the robot can acquire sensory data useful to increase its knowledge about the world.

It is possible that proposals of different agents don't agree, or that they are mutually incompatible.

For example the "corners representation agent", using its own exploration strategies, can generate a proposal corresponding to a place which in the Occupancy Grid has an high probability to be occupied.

4.2.Negotiation Process

In order to reject such a proposal, every "representation agent" is asked to review the proposals generated from all the other ones. In such a way every agent can express a consensus with the proposals of other agents based on its knowledge and the requirements of its own strategies.

If an agent formulate a proposal that is incompatible with the knowledge of some other agent, it can even

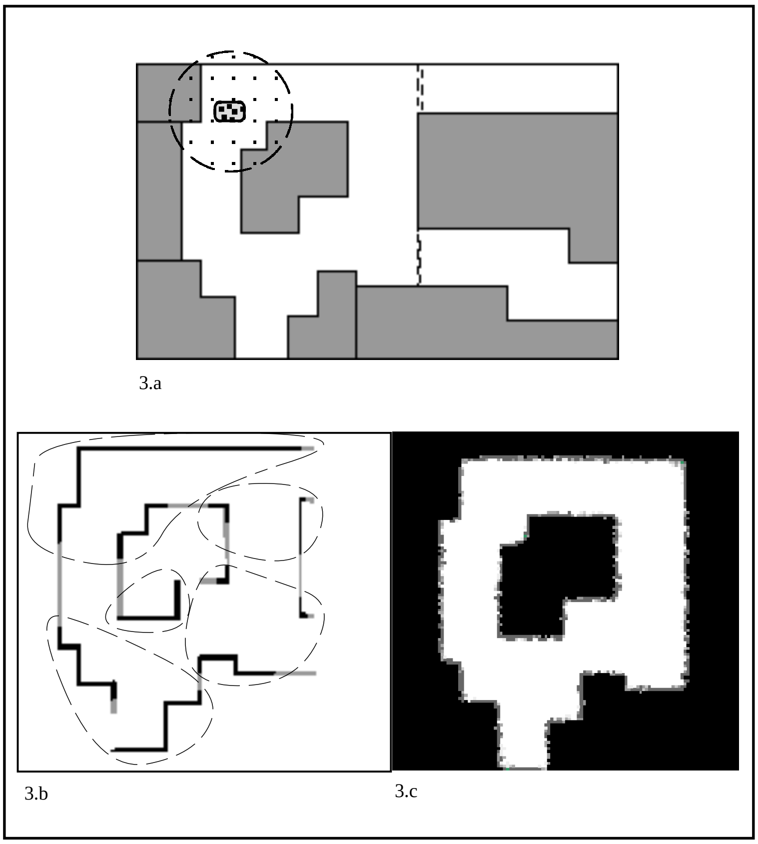

Fig. 3 - The simulated environment 3.a, the diktiometric representation 3.b and the occupancy grid 3.c.

relax some individual preference and generate a counter-proposal, in order to find a mutually acceptable solution. If several proposals are acceptable, it will be chose the proposal with maximum consensus. This negotiation process is democratic in the sense that it looks for the general agreement among the different requirements of every local strategies. A similar negotiated mechanism was already developed by Lander and Lesser in a more general and theoretical way. In [8] they presented a distributed-search algorithm, “negotiated search”, that uses conflict as a source of control information for directing search activity across a set of heterogeneous agents in their quest for a mutually acceptable solution. Our approach takes into account their results.

The presented collaboration schema called “Proposal Mechanism” involves at any time several agents, that interact and share resources; in many situations an agent coordinates its activity with another by synchronizing its action with respect to the other. This synchronization is achieved by exchanging information on the blackboard and sending control messages. The description of the implementation exceeds the scope of this paper.

5. CONCLUSION AND RESULTS

We have presented a new approach to world-modeling based on an extension of diktiometric representations. The use of internal relation allow us to introduce in the merging process information as angular width and distances from corners, information affected only by sensor uncertainty.

Diktiometric representation and internal relations allow us to obtain a network of geometrical representation in which the uncertainty is locally bounded. An appropriate interaction-schema, based on a distributed control architecture, was presented allowing to integrate the world knowledge represented and managed by different representation agents.

Fig. 3 shows snapshots of the user interface during the EXPLORER activity. Fig. 3.a shows the simulated environment. The dashed lines represent obstacles not visible by the laser range finder sensor, but visible with the sonar sensor. Fig. 3.b and 3.c show respectively the diktiometric representation and the occupancy grid during the exploration.

The dashed lines in Fig. 3.b individuate the different extended and local views. The right-hand side of the environment is not reachable by the robot. Only SONMAP has this information. The integration of this representation determinate the robot to explore only the reachable zone of the environment. A high degree of consistency between the diktiometric representation and the simulated environment can be observed.

The presented approach was tested in simulation. The simulation results show that the robot may successfully represent an indoor environment. Currently we are developing real experiments with one of the mobile robots of the PM-AI&R Laboratory. The present implementation of the EXPLORER project runs on a workstation SUN.

6. REFERENCES

[1] Engelson S.P and McDermott D.V., Error Correction in Mobile Robot Map Learning, *Proc. IEEE International Conference on Robotics and Automation*, Nice (1992), pp. 2555-2560.

[2] Durrant-Whyte H.F., Integration, Coordination and Control of Multi-Sensor Robot Systems, *Kluwer Academic Publishers, 1988.*

[3] Kuypers B.J, Byun Y., A robot exploration and mapping strategy based on a semantic hierarchy of spatial representations, *Robotics and Autonomous System* 8 (1991), pp. 47-63.

[4] Brooks R. and Connel J., Asynchronous Distributed Control System for a Mobile Robot, *Proc. Eds. W. Wolfe and N. Marquina SPIE Mobile Robots*, Bellingham, Wash (1986), pp. 77-84.

[5] Elfes A. Dynamic Control of Robot Perception Using Multi-Property Inference Grids, *IEEE Proceedings of the 1992 IEEE International Conference on Robotics and Automation*, Nice France, May 1992, pp. 2561-2567.

[6] Davis E., Representing and Acquiring Geographic Knowledge, *Morgan Kaufmann Publishers, 1986.*

[7] Taylor C.J.and Kriegman D.J., Exploration Strategies for Mobile Robots *IEEE Robotics and Automation 2/3, 1993, pp.248-253.*

[8] Lander S.E. and Lesser, Understanding the Role of Negotiation in Distributed Search Among Heterogeneous Agents, *IJCAI 93 1/2 Distributed AI, pp 438-444.*

[9] Preciado A., Meizel D. et al., Fusion of Multi-Sensor Data: a Geometric Approach, *Proc. IEEE International Conference on Robotics and Automation*, Sacramento, California, April 1991, pp. 2806-2811.

[10] Ayache N. and Faugeras O.D., Maintaining Representations of the Environment of a Mobile Robot, *IEEE Trans. on Robotics and Automation 5(6), December 1989, pp. 337-350.*

[11] Borghi G., Distributed Organization of Hybrid Modules to Generate Plans in Dinamic Environments for an Autonomous Mobile Robot, *Tech.. Rep #94_003, Dipartimento di Elettronica e Informazione Politecnico di Milano - Italy, 1994.*